FINAL REPORT

Title: Effects of scale for assessing fuel treatment effectiveness and recovery post-fire in ponderosa pine

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Eva K. Strand

University of Idaho, College of Natural Resources

Jessie M. Dodge

University of Idaho, College of Natural Resources

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List of Abbreviations/Acronyms

NDVI: Normalized Difference Vegetation Index (NDVI)

dNDVI: differenced Normalized Difference Vegetation Index (NDVI)

NPV: non-photosynthetic vegetation

MTBS

GIS: Geographic Information System

BARC: Burn Area Remote Classification

NBR: Normalized Burn Ratio

EVI: Enhanced Vegetation Index

Keywords

QuickBird, Landsat TM, burn severity, NDVI, scale, ponderosa pine, fuel reduction treatments

Acknowledgements

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Abstract

With the past century of fire suppression in ponderosa pine (*Pinus ponderosa*) forests, there has been an accumulation of surface fuels, causing decreases in understory vegetation and increasing high severity fire risk. However, fire size and location can make it costly and unsafe to obtain ground measurements of understory vegetation cover and fuels. Remotely assessing heterogeneity and ground cover components within a fire perimeter can contribute in monitoring ecological trends post-fire. Landsat TM images are free, have a spatial resolution of 30 m, and have been used to assess burn severity since 1984 whereas the QuickBird sensor has a high spatial resolution of 0.6 to 2.4 m, though it has fewer bands, images take up more space, and take longer to process. This study sought to compare remotely sensed attributes related to burn severity, derived from QuickBird and Landsat TM images, to determine which images correlated more strongly to ground measurements as well as determine if effects of pre-fire fuel reduction treatments could be observed better at finer scales. The 2007 Egley Fire Complex of eastern Oregon prompted the Malheur National Forest to obtain QuickBird coverage of the fire complex at 0.6 m resolution July 26th, August 8th and August 13th, 2007. In 2008, overstory tree canopy cover and understory cover of green vegetation, non-photosynthetic vegetation (NPV), rock, soil and char were measured in 70 field sites. Sites were broadly distributed across elevation, aspect, and the burn severity gradient, determined using a rapid response, Burn Area Remote Classification (BARC) map based on immediate post-fire dNBR values. Field data were collected at five plots distributed within each site. Spearman's rank correlations were used to correlate the Normalized Differenced Vegetation Index (NDVI) derived from QuickBird fine-scale (0.6 m) and Landsat TM 2007 (August 22nd, 2007) and 2008 (July 7th, 2008) images to surface variable covers. To determine the effects of spatial scale, we used focal statistic means in ArcMap at varying window sizes (1 x 1, 3 x 3, 5 x 5, 8 x 8, 17 x 17, 25 x 25, 50 x 50, 83 x 83, 167 x 167, and 417 x 417 pixels) of QuickBird imagery. We found considerable variation of NDVI correlation to surface covers among plots, though NDVI correlations became stronger with tree canopy cover, understory green, soil, and NPV as the window size increased. Site level correlations between NDVI and surface variable covers were much stronger than plot level correlations but were fairly consistent in strength of correlations among scales. QuickBird and Landsat TM NDVI correlations to tree canopy cover, NPV, and soil at the plot and site level were much stronger in untreated sites than treated sites and were generally stronger at fine QuickBird scales (1x1 to 5x5 pixel windows) than broad QuickBird scales (50 x 50 through 417 x 417 windows), though were still similar to Landsat 2007 and 2008 correlation coefficients. This study demonstrates the importance of matching pixel size of remote sensing images to field data scale. We also found that NDVI extracted from Landsat images are remarkably similar to QuickBird data, both at fine and resampled to broad scale, in the Egley Fire Complex (2007).

1. Objectives

With the past century of fire suppression in ponderosa pine (*Pinus ponderosa* Lawson & C. Lawson) forests, there has been an accumulation of surface fuels and dense stands of saplings and seedlings. This has led to a decrease in understory vegetation cover (Covington and Moore 1994; Allen 1998) and an increase in fuel loads, increasing the potential of future high severity fires (Kilgore 1981; Covington and Moore 1994). To reduce the size and severity of wildfires and restore fire resilience in ponderosa pine forests, land managers have implemented fuel treatments, such as mechanical thinning and prescribed fire that focus on ladder fuels (Covington and Moore 1994; Fulé et al. 1997; Agee and Skinner 2005). Thinning tree canopies sometimes increases understory productivity and diversity by giving understory plants greater light access (Bartuszevige and Kennedy 2009; Schwilk et al. 2009). However, mechanical treatments can leave slash, contributing to surface fuels that may increase fire severity (Graham et al. 1999). Managers may choose to burn slash piles, causing soil patches to endure intense heating for extended periods of time, reducing seed viability and slowing plant establishment within those patches (Graham et al. 1999; Korb et al. 2004). Soil disturbances caused by thinning also tends to increase the cover of invasive species (Korb et al. 2004; Stephens et al. 2012). Through the use of proper fuel reductions, fire resilience in ponderosa pine forests can be restored by increasing understory vegetation diversity, specifically fire resilient bunchgrasses and forbs, shifting the fire regime from uncommon large high severity fires back to historical low-severity surface fires (Cooper 1960; Covington and Moore 1994; Fulé et al. 1997).

Fire size and location can make it costly and unsafe to obtain ground measurements of understory vegetation cover and fuels (Lentile et al. 2006). Remotely assessing heterogeneity and ground cover components within a fire perimeter can contribute to monitoring of ecological trends post-fire and are often used to plan and prioritize fuel treatment implementation (Morgan et al. 2001; Robert E. Keane et al. 2001). Landsat TM images are free, have a spatial resolution of 30 m, and have been used to assess burn severity since 1984 (Morgan et al. 2014). However, because of the spatial resolution of Landsat TM images, it is difficult to distinguish between overstory and understory post-fire effects. The QuickBird sensor of Digital Globe Inc. (Longmont, CO), is one of many fine scale sensors with a high spatial resolution of 2.4 m and a panchromatic resolution of 0.6 m. Therefore, with QuickBird imagery or other fine scale sensors, wildfire effects on vegetation can be assessed at finer scales, potentially gathering important ecological data in areas that would be difficult to obtain with ground crews or through the moderate spatial resolution of Landsat imagery. Pre-wildfire fuel reduction treatment effects on post-wildfire understory can also be assessed at fine scales including fire severity, fire consumed fuels, and post-fire understory vegetation growth can be assessed between treated and untreated areas remotely.

In the summer of 2007, a lightning storm in the Malheur National Forest of eastern Oregon caused the Egley Fire Complex – which burned approximately 56,802 hectares (Figure 1). The Egley Fire Complex prompted the forest planner of the Malheur National Forest near Burns, OR to obtain QuickBird pan-fused coverage of the entire fire complex at 0.6 m resolution. These fine scale QuickBird images provided an opportunity to measure how treatments affected initial burn severity or immediate post-fire understory components like fuel loadings and understory vegetation recovery, and to evaluate the ability of QuickBird imagery to determine post-fire understory effects. Therefore, the objectives of this study were to 1) determine if fine scale imagery (QuickBird 0.6 m resolution) correlate better to field measured surface cover variables (tree canopy, understory green vegetation, non-photosynthetic vegetation [NPV], soil, rock, and char cover) than moderate scale imagery (Landsat 30 m resolution) and 2) evaluate QuickBird and Landsat NDVI correlations to field measured surface cover variables in treated and untreated sites. We predict that the high resolution of QuickBird imagery will correlate to field measured surface cover variables better than Landsat TM imagery. Also, because we found untreated sites to have burned at higher severity than treated sites (Dodge et al. 2019), we suggest that QuickBird and Landsat TM NDVI correlations to surface cover variables will be stronger in untreated sites than treated, particularly correlations with QuickBird data.

2. Background

Landsat TM imagery has a medium spatial resolution of 30 m, has seven sensor bands, and has a 16-day revisit time. The accessibility of Landsat TM images make it widely used for measuring post-fire ecological change (Lentile et al. 2006; Morgan et al. 2014). In contrast, QuickBird imagery has a panchromatic spatial resolution of 0.65 m and a multi-spectral resolution of 2.4 m. There are five sensor bands total and has a 1 to 3.5-day revisit time. However, these specifications make QuickBird imagery relatively expensive (US$22 for 54 km^2), especially compared to Landsat imagery. Although, the increased spatial resolution of QuickBird has the potential to increase the accuracy of remotely sensed estimates and provide additional information. Holden et al. (2010) found that QuickBird data correlated strongly with ground-based burn severity estimates within the Gila wilderness of New Mexico and Mallinis et al. (2014) found that QuickBird based fuel type classification had higher overall accuracy compared to EO-1 Hyperion and Landsat TM (both satellites; 30 m resolution) fuel type classifications in the Cholomontas mountains in Central Macedonia. However, the usefulness of QuickBird imagery to determine initial fine scale effectiveness of fuel treatments and their effects on post-fire understory recovery still needs to be addressed.

There have been many different remote sensing indices used to estimate burn severity (Morgan et al. 2014). One of the most common ways to remotely measure burn severity is through the use of the normalized burn ratio (NBR), a burn severity index estimated by taking the difference between near infrared (NIR) band from the shortwave infrared (SWIR) 1 band and then dividing that by their sum, typically from Landsat images. However, the NBR index uses Landsat’s shortwave infrared band, hypothesized to be less susceptible to scattering effects of smoke, a band that the QuickBird sensor does not have.

Another common index used to monitor burn severity is the Normalized Differenced Vegetation Index (NDVI). The NDVI is widely used to monitor vegetation trends (Goward et al. 1985; Myneni et al. 1997), especially post-fire vegetation recovery (White et al. 1996; Henry and Hope 1998; Diaz-Delgado et al. 2003). The NDVI is a vegetation index estimated by taking the difference between the NIR band and the red band and dividing it by the sum of the NIR band and the red band. One of the benefits of using the NDVI over NBR is that it can be compared across most satellite sensors including Landsat TM and QuickBird (Hudak et al. 2007). Hudak et al. (2007) found that NDVI did not significantly differ from NBR, suggesting NDVI can be used as a substitute. Therefore, for this study, NDVI will be used to analyze burn severity in both Landsat and QuickBird imagery.

3. Materials and Methods

3a. Study area

Our study area was within the Malheur National Forest of eastern Oregon, USA (Figure 1a and b), approximately 688,000 hectares (ha) of ponderosa pine forests, mixed conifer forests, high desert grasslands, sagebrush (*Artemisia* spp. L.) steppe and western juniper (*Juniperus occidentalis* Hook.) woodlands (Dodge et al. 2019). Our study area ranged approximately 40 to 70 km from Burns, OR (approximately 43° 52' 50" N, 119° 38' 24" W). Elevation ranged from 1506 m to 1755 m above sea level. Mean high temperature in the growing season (May through August) is 26°C and the mean low temperature in winter (November through February) is -8°C. Mean annual precipitation is 279 mm (US Climate Data 2019). Ponderosa pine was the dominant tree species in our study area.

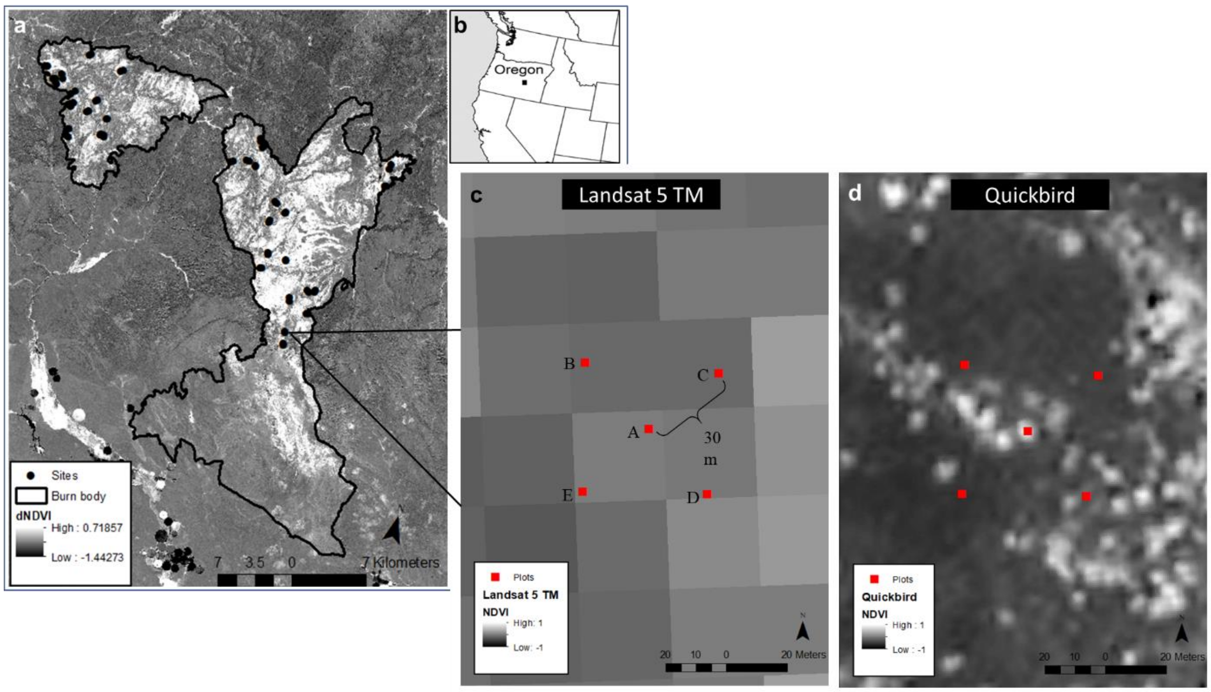

Figure 1. Egley Fire Complex (2007) of eastern Oregon, USA, showing (a) the gradient of burn severity represented by dNDVI (pre-fire NDVI – immediate post-fire NDVI), (b) location of study area in Oregon, USA, (c) plot layout within sites (5 plots per site) over Landsat 2007 NDVI image, and (d), plot layout within site over QuickBird 2007 NDVI image.

The Egley Fire Complex burned approximately 56,800 ha from 7 to 21 July 2007 (Figure 1a). Prior to the Egley Complex, the Malheur National Forest implemented vegetation and fuel treatments for vegetation management and wildfire protection objectives beginning in 1985. Treatment units were recorded as polygons in a Geographic Information System (GIS). Pre-fire silvicultural or fuel reduction treatments within the Egley Fire Complex perimeter included commercial harvests (7,280 ha), pre-commercial thinning (6,855 ha), slash and pile burns (6,853 ha), and understory prescribed burns (1,566 ha). For this study, all sites that had some form of fuel reductions including commercial harvests, pre-commercial thinning, slash and pile burns, understory prescribed burns, or prior wildfires were categorized as treated sites to compare with untreated sites (Dodge et al. 2019).

3b. Field Methods

In the summer of 2008 (one-year post-fire), 35 paired sites (35 treated and 35 untreated) were established (Figure 1a). Sites were broadly distributed across elevation, aspect, and a burn severity (unburned, low, moderate, or high) gradient (Figure 2). A rapid response, Burn Area Remote Classification (BARC) map based on immediate post-fire dNBR values (Parsons and Orlemann 2002) was used as a guide to distribute field sites along the burn severity gradient. In the immediate post-fire BARC map, low burn severity corresponds to predominantly green (live) tree crowns, moderate burn severity corresponds to predominantly brown (scorched) tree crowns, and high burn severity corresponds to predominantly black (charred) tree crowns (Hudak et al. 2011). Paired treated/untreated sites (n=35 each) were distributed across the burn severity gradient at locations guided by four criteria, described in Dodge et al. (2019). As described by Hudak et al. (2011), each site consisted of a central (plot A), 1 m^2, plot and four additional (B, C, D, and E) 1 m^2 quadrats situated orthogonally 30 m from the center plot and oriented to the prevailing slope. Sites were situated this way to represent a cluster of three to five Landsat pixels (Figure 1c).

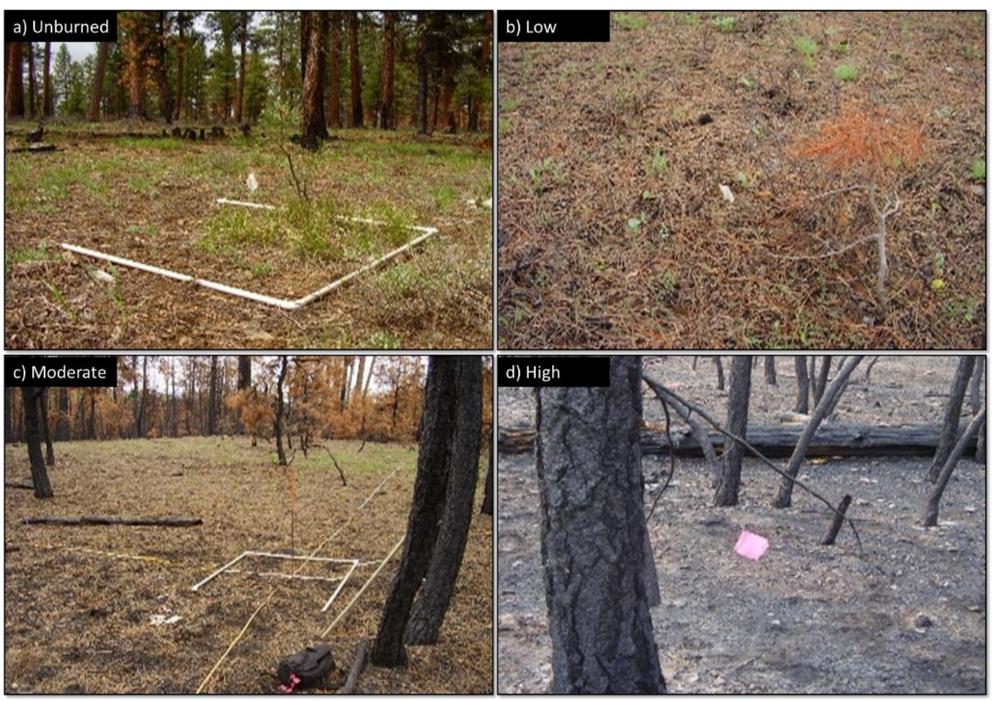

Figure 2. Plot level field photos (2008) of an (a) unburned site, (b) low burn severity site, (c) moderate burn severity site, and (d) a high burn severity site within the Egley Fire Complex (2007) of eastern Oregon, USA.

Surface measurements (tree canopy, understory green vegetation, NPV, soil, rock, and char cover) were measured at each of the five plots within a site (n=350 plots). Tree canopy cover was estimated using a convex spherical densiometer facing each cardinal direction around each plot, then averaged to plot level. Understory green vegetation, NPV, soil, rock, and char cover (%) were estimated in five 1 m^2 quadrat plots at each site. The location of each plot (A, B, C, D, and E) were recorded with a Trimble GeoX Global Positioning System unit with a < 0.5 m spatial accuracy.

3c. Remote Sensing Data

QuickBird pan-fused and orthorectified images were acquired from Digital Globe Inc (Longmont, CO). QuickBird images of the 2007 Egley Fire Complex were taken on July 26th, August 8th, and August 13th, 2007. Landsat 5 TM images (from here on out, Landsat) were radiometrically corrected and acquired from EarthExplorer USGS (EarthExplorer.usgs.gov). Landsat TM 5 images of the Egley Fire Complex were taken on July 18, 2006 (one-year pre-fire), August 22, 2007 (immediately post-fire), and July 7, 2008 (one-year post-fire). Using Ersi ArcMap 10.6.1 (ArcMap/Windows/Image Analysis), the normalized vegetation difference index (NDVI) was calculated for each image (equation 1).

$$NDVI = \frac{(NIR-RED)}{(NIR+RED)} \quad (1)$$

Because QuickBird pixels (0.6x0.6 m) were smaller than field plots (1 m^2) and to determine if scale correlations to surface cover had a threshold, QuickBird images were averaged using focal statistic means in ArcMap (ArcToolbox/Spatial Analyst Tools/Neighborhood/Focal Statistics) at various window sizes (Table 1). Normalized vegetation difference indexes were then extracted for each plot within each QuickBird window size and Landsat 5 TM images (left at 30x30 m resolution). Spearman's rank correlations, using the "Hmisc" package in R software (Harrell 2007) were used to correlate each plot's NDVI values extracted from QuickBird window sizes and Landsat TM 5 2007 and 2008 images to field measured surface cover variables, matching to the corresponding plot measured surface cover variables. For example, NDVI values extracted from plot A, site 31 within a QuickBird window size of 5 x 5 pixels were correlated to field recorded surface covers measured in plot A, site 31. For site level analyses, NDVI values extracted from each plot were averaged to site for each QuickBird window pixel size and Landsat image to be correlated to surface cover variables averaged to the site level.

Table 1. QuickBird window sizes (pixels) used for scale differences and their corresponding meter by meter (m^2) size.

Window size (pixels)	m	Scale Similarity
1x1	0.6x0.6	
3 x 3	1.8x1.8	
5 x 5	3.0x3.0	
8 x 8	4.8x4.8	
17 x 17	10.2x10.2	Spot
25 x 25	15.0x15.0	
50 x 50	30x30	Landsat TM
83 x 83	49.8x49.8	
167 x 167	100.2x100.2	
417 x 417	250.2x250.2	MODIS

Results and Discussion

QuickBird and Landsat NDVI correlations (Objective 1)

Correlations between NDVI and surface cover measurements from field data varied slightly among plots, except NDVI and char cover correlations which were considerably lower at plots A and B than the other three plots (Figure 3). Tree canopy cover correlations to NDVI values were significant at all scales within all plots (all $\rho \geq 0.35$, all $P \leq 0.003$, Figure 3a). Understory green vegetation cover correlations varied in strength among different QuickBird window sizes and Landsat 2007 and 2008 NDVI, but generally became stronger as the spatial scale of the remote sensing data increased; QuickBird windows 17 x 17 through 417 x 417 and Landsat 2007 and 2008 NDVI values were significantly correlated to understory green vegetation (all $\rho \geq 0.24$, all $P \leq 0.046$) except QuickBird windows 17 x 17, 25 x 25, 167 x 167, and Landsat 2007 for plot B and QuickBird window 417 x417 for Plot D (Figure 3b). Only at plot C and D were fine scale (windows 1 x1 and 3 x 3) NDVI values significantly correlated to understory green cover (all $\rho \geq 0.25$, all $P \leq 0.038$, Figure 3). Non-photosynthetic vegetation and soil cover correlations to QuickBird and Landsat NDVI values followed similar trends to understory green vegetation cover, with stronger correlations at broader scales, though were generally more significant at finer scales than understory green (all $\rho \geq 0.24$, all $P \leq 0.042$), except QuickBird windows 1 x 1 through 8 x 8 NDVI correlations to NPV and soil within plot C, QuickBird windows 5 x 5, 8 x 8, and 417 x 417 NDVI correlations to NPV within plot D, and Landsat 2008 NDVI correlations to NPV within plot B (Figure 3c and d). Char cover correlations to NDVI values were only significant at plots C at all scales, plot D at QuickBird windows 25 x 25 through 417 x 417 and at Landsat 2008, and plot E at Quickbird window 417 x 417 (all $\rho \leq -0.26$, all $P \leq 0.032$, Figure 3e). Rock cover correlations to NDVI values were only significant within plot E at QuickBird windows 83 x 83, 167 x 167, 417 x 417 (all $\rho \leq -0.24$, all $P \leq 0.042$), and Landsat 2008 ($\rho = -0.34$, $P = 0.004$).

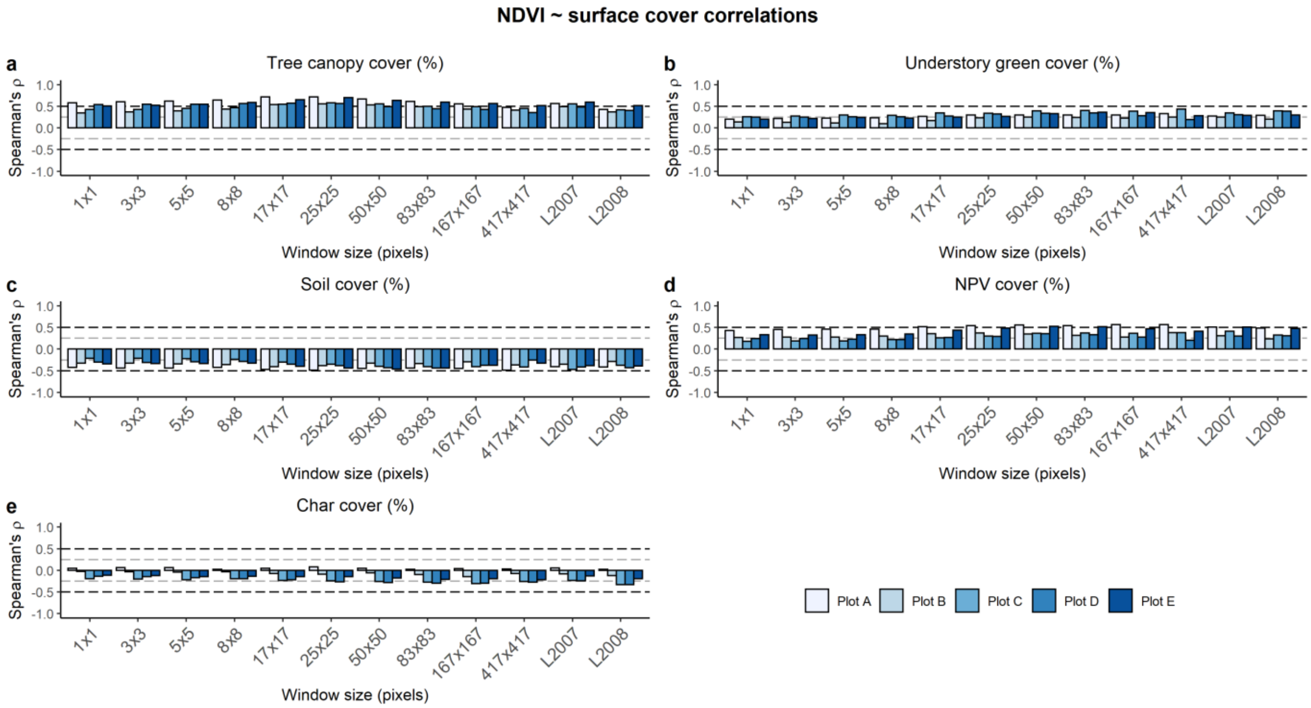

Figure 3. Spearman's rank correlation (ρ) of QuickBird window sizes (pixels) and Landsat 2007 (L2007) and Landsat 2008 (L2008) Normalized Differenced Vegetation Index (NDVI) values by (a) tree canopy, (b) understory green, (c) non-photosynthetic vegetation (NPV) cover, (d) soil, and (e) char cover (%) by all plots within a site. Light gray dotted lines denote correlations with $\rho \geq 0.25$ or $\rho \leq -0.25$ and $P \leq 0.05$ and black dotted lines denote correlations with $\rho \geq 0.50$ or $\rho \leq -0.50$ $P \leq 0.001$. Note, rock cover was omitted due to lack of significance.

We expected to see stronger correlations between understory surface cover variables and finer scale QuickBird windows because they were similar in scale to our plots, however, broader scale NDVI correlations to surface cover variables were generally stronger. Overstory shading effects may be skewing fine scale NDVI correlations to understory surface cover variables here as well (Asner and Warner 2003; Lifu Zhang et al. 2015). Surface cover variables were also measured one-year post-fire, giving understory green an extra year to grow post-fire, obscuring soil, NPV, and char cover.

Correlations between NDVI values and surface cover variables were generally much stronger when field plot data was averaged to the site level (average cover within the 5 plots nested within site). Site level NDVI correlations to soil and NPV were slightly stronger at then plot A level correlations (site: all scales NPV $\rho \geq 0.52$, all soil $\rho \geq -0.48$; plot: all NPV $\rho \geq 0.43$, all soil $\rho \geq -0.41$, all $P < 0.001$; Figure 4c and d). Site level NDVI correlations to understory green vegetation (all $\rho \geq 0.43$; all $P < 0.001$; Figure 4b) and char cover (all scales $\rho \leq -0.32$, all $P \leq 0.007$; Figure 4e) were much stronger than plot A correlations (all $\rho \geq 0.27$; all $P \leq 0.027$ for understory green). Note, plot A had the poorest NDVI correlations to char cover out of all five plots studied, which explains why plot vs. site NDVI correlations to char cover are so poor at the plot level. However, plot A NDVI correlations to tree canopy cover were slightly stronger than site level correlations at the 17 x17, 25 x 25, and 50 x 50 window sizes (all $\rho \geq 0.70$ for plot A, ρ

≥ 0.64 for site, all $P < 0.001$). QuickBird 1 x 1 and 3 x 3 window sizes were expected to be the more strongly correlated to surface cover variables, especially at the plot level, because they were more similar in scale to the 1 m^2 field plot size, however, moderate scale window sizes (17 x 17 through 50 x 50 QuickBird window sizes and Landsat) tended to have the strongest correlations to surface cover variables (all $\rho \geq 0.27$ for tree canopy, understory green, and NPV, all $\rho \leq -0.41$ for soil and char, all $P < 0.001$), except Landsat 2008 NDVI correlations to tree canopy cover at both Plot A and the site scale (Figure 4).

When comparing similar resolution at the site level (Landsat and QuickBird 50 x 50 window size), Landsat 2007 NDVI values had stronger correlations to tree canopy, NPV, and soil cover ($\rho \geq 0.53$ for tree canopy and NPV cover, $\rho = -0.54$ for soil cover, all $P < 0.001$) than QuickBird 50 x 50 window sizes ($\rho \geq 0.51$ for tree canopy and NPV cover, $\rho = -0.50$ for soil cover, all $P < 0.001$; Figure 4). Although, site level QuickBird 50 x 50 window size NDVI correlations to understory green ($P < 0.001$, $\rho = 0.51$) were stronger than Landsat 2007 NDVI correlations ($P < 0.001$, $\rho = 0.46$ for understory green; Figure 4). At Plot A, however, QuickBird 50 x 50 window size NDVI correlations to all surface cover groups (except rock and char, [$\rho \geq 0.30$ for tree canopy, understory green, and NPV cover, $\rho = -0.45$ for soil cover, all $P \leq 0.012$]) were stronger than Landsat correlations ($\rho \geq 0.27$ for tree canopy, understory green, and NPV cover, $\rho = -0.41$ for soil, all $P \leq 0.022$; Figure 4).

We expected to see stronger correlations at the site level because we averaged plot level variability. Site level correlations are going to be stronger when you have more variability in the landscape pattern. However, we were surprised to see Landsat correlations to surface covers, especially tree canopy, NPV, and soil cover, were stronger, if only slightly, than QuickBird correlations, even when resampled to the same spatial scale as Landsat (30 m). This might be explained by the site layout choice, which was chosen to represent a cluster of Landsat pixels. The spatial accuracy of any single plot location also become less important when plots were averaged to the site level. Clearly, even with high-accuracy GPS equipment, it is very difficult to map a plot to < 1 m accuracy and to georeferenced an image to exactly coincide with that 1 m^2 plot. All surface variables were measured one-year post-fire whereas the QuickBird images were taken immediately post-fire, which also may have affected QuickBird NDVI correlations to surface cover variables.

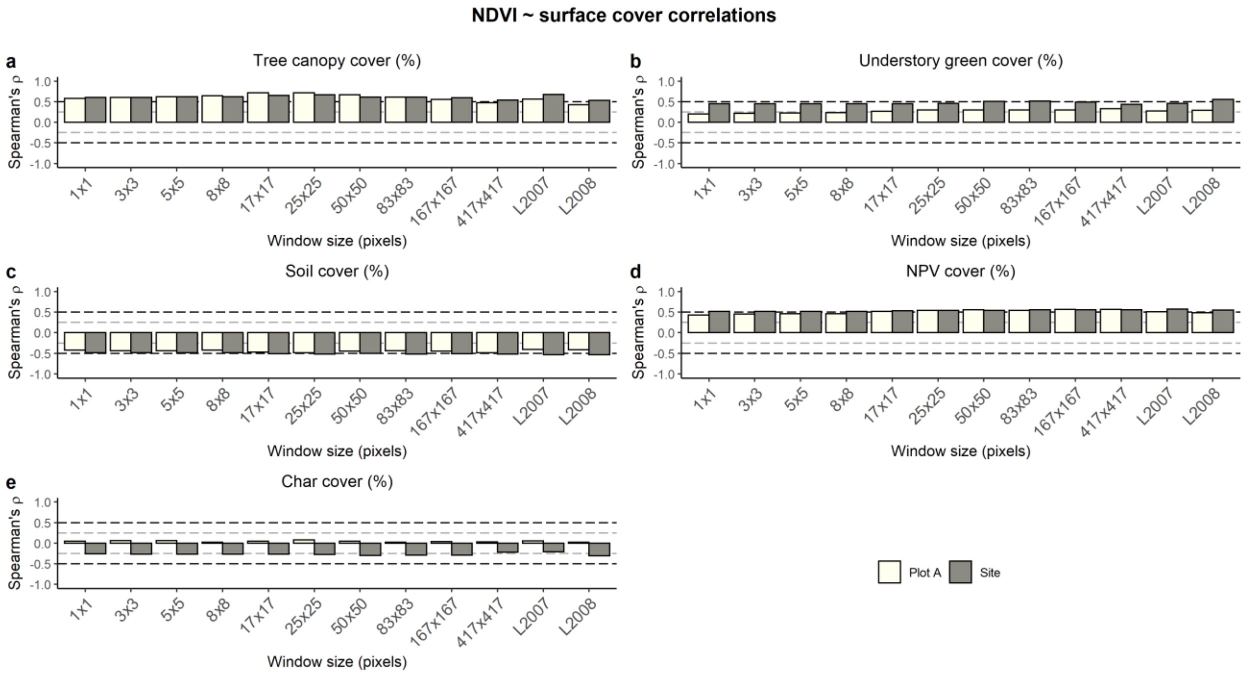

Figure 4. Spearman's rank correlations (ρ) of QuickBird window sizes (pixels) and Landsat 2007 (L2007) and Landsat 2008 (L2008) Normalized Differenced Vegetation Index (NDVI) values by (a) tree canopy, (b) understory green, (c) non-photosynthetic vegetation (NPV) cover, (d) soil, and (e) char cover (%) by center plot A (Plot A) and all plots averaged to site (Site). Light gray dotted lines denote correlations with $\rho \geq 0.25$ or $\rho \leq -0.25$ and $P \leq 0.05$ and black dotted lines denote correlations with $\rho \geq 0.50$ or $\rho \leq -0.50$ $P \leq 0.001$. Note, rock cover was omitted due to lack of significance.

Treated vs Untreated QuickBird and Landsat NDVI correlations (Objective 2)

Surface cover and NDVI correlations were stronger within untreated sites than treated sites across all scales (Figure 5). Tree canopy cover and soil were strongly correlated to all scales of NDVI in untreated sites ($\rho \geq 0.74$ for tree canopy cover at all scales, $\rho \leq -0.67$ for soil cover correlations at all scales, $P < 0.01$ at all scales) than treated sites (both $\rho \geq 035$, both $P \leq 0.041$ for tree canopy cover within QuickBird 25 x 25 window and Landsat 2007, all $\rho \leq -0.30$, all $P \leq 0.029$ for soil cover; Figure 5a and d). The same trend was observed in NPV cover and NDVI correlations; untreated sites (all $\rho \geq 0.67$, all $P < 0.001$) had stronger correlations than treated sites (all $\rho \geq 0.45$, all $P \leq 0.008$), though only at finer QuickBird scales (1 x 1 through 8 x 8 window sizes) after which, NPV cover was only slightly more correlated to NDVI values within untreated sites (all $\rho \geq 0.63$, all $P \leq 0.001$) than treated sites (all $\rho \geq 0.57$, all $P < 0.001$; Figure 5d). Understory green vegetation cover correlations to NDVI values were similar in strength, though slightly stronger in untreated (all $\rho \geq 0.42$, all $P \leq 0.011$) than treated sites (all $\rho \geq 0.35$, all $P \leq 0.041$). However, char cover and NDVI correlations were significant at all scales within treated sites except for Quickbird 417 x 417 and Landsat 2007 scales (all $\rho \geq 0.36$, all $P \leq 0.035$,) but were only significant at the Quickbird 167 x 167 window within untreated sites ($\rho = -0.34$, all $P = 0.045$).

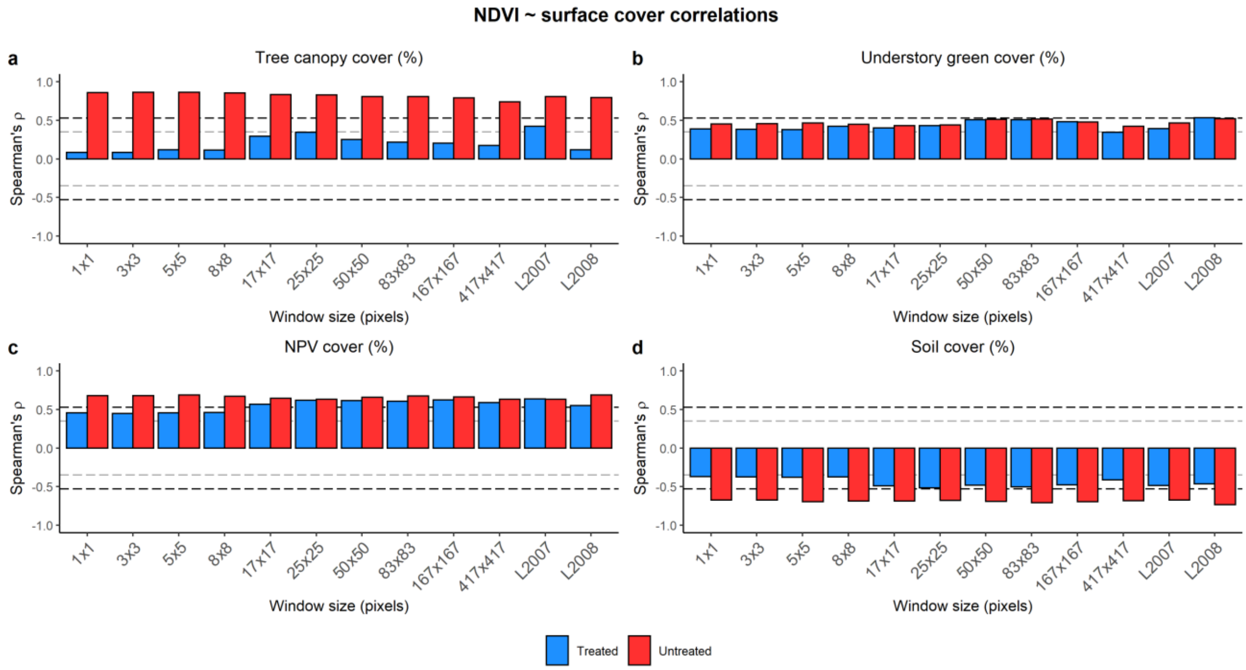

Figure 5. Site level Spearman's rank correlation (ρ) of QuickBird window sizes (pixels) and Landsat 2007 (L2007) and Landsat 2008 (L2008) Normalized Differenced Vegetation Index (NDVI) values between treated (T) and untreated (U) sites for (a) tree canopy, (b) understory green, (c) non-photosynthetic vegetation (NPV) cover, and (d) soil (%) aggregated by site. Light gray dotted lines denote correlations with $\rho \geq 0.35$ or $\rho \leq -0.35$ and black dotted lines denote correlations with $\rho \geq 0.55$ or $\rho \leq -0.55$. Note, correlations with $\rho \geq 0.35$ or $\rho \leq -0.35$ were significant at $P \leq 0.05$ and correlations with $\rho \geq 0.53$ or $\rho \leq -0.53$ were significant at $P \leq 0.001$. Both char and rock cover were omitted due to lack of significance.

The observed stronger correlations between satellite imagery and field data in untreated sites compared to treated sites might be explained by burn severity. Dodge et. al. (2019) showed that untreated sites that burned at low severity had significantly higher tree canopy cover than treated sites that burned at low severity and untreated sites that burned at high severity (Note, the same data from Dodge et al (2019) was used in this project). Dodge et al. (2019) also showed that untreated sites burned at higher severity than treated sites; only five of the thirty-fire treated sites burned at high severity, whereas twenty-four of the thirty-five untreated sites burned at high severity. The stronger NDVI correlations to tree canopy cover seen in untreated sites compared to treated sites is most likely due to the drastic extremes of tree canopy cover found within untreated sites; there was either very high canopy cover (unburned-low severity) or no tree canopy cover (high severity). This could also explain the stronger NDVI correlations to soil cover within untreated sites as well; either there was a considerable amount of soil exposed (high severity) or little to no soil exposure (unburned-low severity). However, it is important to note that treated sites that burned at high severity had significantly more exposed soil cover than low severity sites, more so than untreated sites that burned at high severity (though not significantly more, Dodge et al. 2019), possibly explaining why the stronger NDVI and soil correlations within untreated sites were not as drastically stronger than correlations within treated sites as seen with tree canopy cover. Understory green, on the other hand, was more influenced by severity than treatment (Dodge et al. 2019), thus explaining why the correlations between NDVI and understory green vegetation were similar between treated and untreated sites. It is possible, that the lack of tree canopy cover in the untreated, high severity sites, minimized shading effects and strengthened understory surface cover correlations to NDVI values. The lower shading effects at high severity may also explain why correlations between NDVI values and soil and NPV surface covers were stronger within untreated site than treated sites at finer scales (QuickBird windows 1 x 1 through 8 x 8).

Conclusions, Management Implications, and Future Research

The normalized vegetation index correlated strongly with tree canopy cover and moderately well with understory green vegetation, NPV, and soil, at various scales, and slightly with char. These results suggest satellite derived NDVI is an accurate approximation of field measurements that relate to burn severity effects on vegetation and soil. However, burn severity is often quantified by measuring soil characteristics such as char depth, organic matter loss, altered infiltration, and color (Lentile et al. 2006) and therefore, in order to measure soil char more accurately, the normalized burn ratio (NBR) might be a better index for measuring burn severity (Lentile et al. 2006; Lentile et al. 2009). However, Hudak et al. (2007) found similar combined Pearson Correlations between post-fire NDVI and NBR values correlated to field measured surface cover variables (green vegetation, rock, mineral soil, ash, and litter) in the Alaska, western Montana, and southern California regions using Landsat images, also suggesting that NDVI could be substituted for NBR.

Site level correlations were much stronger than at plot level, demonstrating the importance of a) having multiple plots within a study site and b) matching pixel size of remote sensing images to the scale of field data collection. Site level QuickBird and Landsat NDVI correlations to surface cover variables were remarkably similar, though plot level QuickBird NDVI correlations were stronger than Landsat 2007 correlations to surface covers. Holden et al. (2010) found similar site level results when predicting dNDVI from one-year post-fire ground measured Composite Burn Index (CBI) measurements between QuickBird (2.4 m resolution) and Landsat TM images of the Dry Lakes Fire Complex within the Gila Wilderness, New Mexico; Landsat TM dNDVI coefficients of determination were slightly stronger than QuickBird dNDVI. However, Holden et al. (2010) found stronger coefficients of determination when predicting differenced Enhanced Vegetation Index (dEVI) using CBI data using QuickBird imagery than Landsat TM imagery. Huete et al. (1997) compared vegetation indices (VI) including NDVI, Soil Adjusted Vegetation Index (SAVI), Soil and Atmospherically Resistant Vegetation Index (SARVI), and an altered SARVI (SARVI2), within multiple Landsat 4 and 5 TM images globally and found that NDVI tended to saturate in densely vegetated areas and NDVI varied appreciably over arid and semiarid regions due to canopy background variations. Huete et al. (1997) suggests using additional vegetation indices (VI) to complement NDVI in vegetation monitoring. It is possible that QuickBird and Landsat NDVI correlations to surface cover variables are similar because NDVI values are sensitive to background variations within pixels. Alternative vegetation indices like SAVI (Huete 1988), atmospherically resistant vegetation index (ARVI) (Kaufman and Tanre 1992), and the Enhanced Vegetation Index (EVI) (Huete et al. 1997) might show different results.

QuickBird and Landsat NDVI site level correlations with tree canopy cover, NPV and soil cover were much stronger in untreated sites than treated sites at all scales, suggesting ecological effects of pre-fire fuel reduction treatments can be monitored remotely. However, results may be misleading; we found stronger NDVI-surface cover correlations within untreated sites than treated sites which may be because treated sites had more variability in burn severity whereas untreated sites tended to either be unburned or burned at high severity (Dodge et al. 2019) Therefore, ground truthing remotely sensed data is highly recommended.

Like QuickBird and Landsat NDVI correlations (Obj 1), moderate scale resolution (QuickBird 17 x 17 through 50 x 50 window sizes and Landsat 2007) NDVI tended to have stronger correlations to surface cover variables. The stronger correlations between NDVI and surface cover variables at larger scales might be explained by the effect of averaging values within a pixel, thus reducing variability and strengthening the correlations. These results suggest Landsat TM images can capture the effects of burn severity at a landscape scale, as measured by NDVI, in forested ecosystems similarly to fine scale remote images, like QuickBird. Landsat TM images are also easily accessible to land managers, have a wide temporal and spectral range and therefore can have a wider application when measuring the effects of wildfire and burn severity. It is extremely difficult to georeference QuickBird imagery to field measured locations with a sub-meter accuracy, making fine-scale imagery harder to ground truth, especially if field measured plots are at a different scale than the QuickBird pixels. However, the strengths of fine resolution imagery may be at smaller scales, i.e. to estimate post-fire tree crown metrics (Klauberg et al. 2019), assessing soil erosion (Meusburger et al. 2010), effectiveness of post-fire treatments (Lewis and Robichaud 2011), and potentially measure vegetation cover within rangeland areas (Everitt et al. 2006).

This study warrants future research into the applications of fine scale imagery when measuring the ecological effects of burn severity, particularly in rangeland areas. Gamon et al. (1995) found that in areas with sparse canopies (leaf area index [LAI] range from 0-2), NDVI was especially sensitive to canopy cover differences, however, NDVI loses its sensitivity in moderate to dense canopies in San Mateo County, CA. Other studies have found difficulty distinguishing understory vegetation from overstory vegetation using NDVI (Law and Waring 1994; Eriksson et al. 2006). In future research, we plan to evaluate how the correlation between satellite derived indices and field measurements varies with tree canopy cover. We expect to see that QuickBird imagery correlates better to surface variable covers than Landsat in areas with low tree canopy cover (i.e. rangelands). These results would give land managers, particularly rangeland managers, an insight on, not only which satellite images would be sufficient in capturing the effects of burn severity on soil and vegetation, but what indexes to use. We will conduct these additional analyses prior to submitting this research for publication.

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Appendix A. Contact information for project personal

PI:

Dr. Eva K. Strand
Department of Forest, Rangeland and Fire Sciences
University of Idaho
875 Perimeter Drive, MS 1133
Moscow, Idaho 83844-1133
evas@uidaho.edu

Student PI

Jessie M. Dodge
Department of Forest, Rangeland and Fire Sciences
University of Idaho
875 Perimeter Drive, MS 1133
Moscow, Idaho 83844-1133
jessied@uidaho.edu

Appendix B. List of delivery products

1. Article in prep for Remote Sensing of Environment
2. This work was presented as a poster at the 2019 Association of Fire Ecology 8th International Fire Ecology and Management Congress: Cultivating Pyrodiversity, Tucson, AZ. "Effects of Scale on Remote Sensing Assessments of Burn Severity in a Ponderosa Pine Forest."
3. Scheduled to present a webinar to the Northwest Fire Science Consortium, February 4th, 2020
4. Scheduled to present a webinar to the Great Basin Fire Science Exchange, March 4th, 2020

Appendix C: Metadata

Field datasets collected in 2008 (Bright et al. 2019) and all Landsat 5 TM images (EarthExplorer.usgs.gov) are publicly available for further analysis. QuickBird images are available upon request to PI or student PI.